Application of Bayesian Based Statistical Prediction in Financial Data Analysis

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Abstract: Financial risk warning has profound theoretical and practical significance for maintaining the healthy development of the economy and ensuring the stable operation of the financial system. Finding a scientific, accurate, and efficient risk measurement method is crucial for improving risk management efficiency and ensuring financial security. In recent years, with the rapid improvement of computing technology and hardware performance, Bayesian statistical inference, as a powerful data analysis tool, has gradually emerged in the field of financial risk management and received increasing attention and application. The Bayesian method, by combining prior information with sample data, can more comprehensively reflect uncertainty and provide a more robust and reliable basis for risk prediction. This article delves into the specific applications of Bayesian based statistical forecasting in financial data analysis. By constructing Bayesian models, we can quantitatively analyze various risks in the financial market. Meanwhile, Bayesian methods can effectively handle complex features such as nonlinearity and non stationarity in financial data, improving the accuracy and timeliness of risk warning.

1. Introduction

With the rapid development of information technology and the continuous innovation of data collection technology, data collection, storage, processing, and analysis have become the focus of attention in various industries [1]. The value conversion ability of data, that is, how to effectively utilize data to insight market trends, optimize decision-making processes, and improve operational efficiency, has become a key indicator for measuring enterprise competitiveness [2]. Among numerous data types, time series data has become one of the most widely studied and researched due to its unique temporal dimension and ordered recording characteristics. In the financial market, time series data plays a crucial role. The financial market is constantly changing, and the changing patterns of financial variables such as price fluctuations, trading volume, and interest rates over time contain rich market information and investment opportunities [3]. Therefore, the research and application of financial time series analysis are of great significance for revealing the operating rules of financial markets, guiding investment decisions, and preventing financial risks [4]. Especially in the context of globalization, the interconnectivity of financial markets is deepening, and financial risks are also showing a trend of cross market and cross-border dissemination.

The long-term accumulation of financial risks may lead to financial crises, seriously endangering financial stability and having far-reaching impacts on many sectors of the economy [5]. Therefore, how to effectively identify, evaluate, and manage financial risks has become an important issue faced by financial regulatory agencies, financial institutions, and investors [6]. However, the distribution characteristics of financial data often deviate greatly from the conventional assumption of normal distribution. A large number of empirical studies have shown that financial data mostly exhibits the characteristic of "peak thick tail", that is, the probability of extreme values (outliers) appearing in the data distribution is relatively high, while the probability density in the central region is relatively low [7]. This characteristic poses many challenges for traditional statistical methods when processing financial data. Simply removing these outliers is unscientific, as they often reflect extreme events and potential risks in financial markets, and are essential information in financial data analysis [8]. Therefore, how to effectively handle outliers in financial data, improve

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the accuracy and robustness of risk measurement, has become an important research direction in financial time series analysis.

Financial risk is objectively present, although it can be perceived, it is difficult to measure accurately. The characteristics of financial risks include high leverage, concealment, and diffusion, which make risk averse investors wary of financial risks. Especially tail risk, which refers to the risk caused by extreme events, poses a serious threat to investors' wealth security due to its low probability and high loss characteristics. Therefore, managing financial risks, especially tail risks, is crucial for investors. In response to the aforementioned challenges in financial data analysis and risk management, this article delves into the specific application of Bayesian based statistical forecasting in financial data analysis. Bayesian methods, as a powerful statistical inference tool, have shown great potential in financial time series analysis due to their unique advantages. By constructing Bayesian models, we can fully utilize prior information and sample data to quantitatively analyze various risks in the financial market.

2. The Application of Bayesian Method in Financial Data Analysis

2.1. Bayesian Method

Bayesian method, rooted in Bayes' theorem, is an advanced means of systematically explaining and solving statistical problems [9]. A comprehensive Bayesian process covers data analysis, construction of probability models, setting of prior information, assumption of effect functions, and final decision-making [10]. The core lies in integrating prior information of unknown parameters with sample data, deriving posterior information based on Bayes' theorem, and then inferring unknown parameters based on these posterior information. The essence of Bayesian analysis lies in the effective utilization of prior information and the careful construction of prior distributions for statistical inference in the process of analyzing practical problems.

Bayesian statistics is deeply rooted in Bayes' theorem, whose fundamental formula is derived from the concept of conditional probability. Conditional probability, usually expressed as $P(A \mid B)$, measures the likelihood of event A occurring under the condition that event B occurs. According to the multiplication rule of probability, we can derive $P(A \cap B) = P(A \mid B)P(B) = P(B \mid A)P(A)$, where $P(A \cap B)$ is referred to as the joint probability of A, B, reflecting the probability of A, B occurring simultaneously. By appropriately modifying the above formula, we can obtain the expression of Bayes' theorem, which takes the following form:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{1}$$

This article uses a Bayesian neural network architecture with a hidden layer to construct a financial risk warning model, aiming to capture the complex nonlinear relationship between financial risk warning indicators and financial risk stress index. Specifically, in the design of this model, 15 nodes are configured in the input layer, corresponding to 15 risk warning indicators $X_1, X_2, \cdots, X_{15}$; The hidden layer contains 3 nodes Z_1, Z_2, Z_3; The output layer has a node that directly corresponds to the financial risk stress index Y. The mapping relationship from the input layer to the hidden layer is described using the following model:

$$\begin{aligned} Z_m &= Sigmoid(\alpha_{0m} + \alpha_{1m}X_1 + \alpha_{2m}X_2 + \cdots + \alpha_{jm}X_j + \cdots \\ &\alpha_{15m}X_{15}) m = 1,2,3 \end{aligned} \tag{2}$$

In this model, α_{jm} represents the connection weight coefficient between the financial risk warning indicator node X_j and the hidden layer node Z_m. The $Sigmoid(x)$ function, as a nonlinear activation function, plays a crucial role in nonlinear mapping in neural network models. It is the core element that enables neural networks to simulate complex nonlinear relationships.

2.2. Specific Applications

In the field of financial time series forecasting, early research mainly relied on empirical and statistical methods for prediction. Empirical methods, such as technical analysis and fundamental analysis, are mostly based on expert experience and market knowledge, and they rely heavily on people's subjective judgments and historical experience. However, in the face of complex, ever-changing, and uncertain financial markets, these methods often seem inadequate, and the accuracy of predictions is difficult to guarantee. With the deepening of financial theory and the development of computing technology, Bayesian methods have gradually emerged in financial data analysis. As a powerful statistical inference tool, Bayesian methods continuously update their posterior knowledge of unknown parameters by introducing prior information and likelihood functions, combined with observational data, in order to achieve accurate prediction of financial time series.

Bayesian methods have demonstrated their unique advantages in predicting overall trends in financial markets. By carefully observing market trends and combining Bayesian methods to establish models of future market changes, investors can gain a deeper understanding of market dynamics and make more accurate decisions. This not only helps to capture market opportunities, but also effectively avoids potential risks. In addition, Bayesian methods also play an important role in the field of financial risk assessment. By analyzing historical and other relevant data, Bayesian methods can determine the probability distribution of financial markets and evaluate the probability and severity of different risk events. For example, key risk indicators such as interest rate changes and stock price fluctuations can be quantitatively analyzed using Bayesian methods. This provides a scientific basis for investors to develop risk management strategies, helping them better control their positions, engage in option trading, and achieve the goal of asset preservation and appreciation.

3. Empirical Analysis

3.1. Comparison of Prediction Accuracy

To verify the effectiveness of the model proposed in this paper, a comparative experiment will be conducted between the model and traditional statistical methods based on fundamental analysis. Figure 1 visually presents the comparison between the Bayesian neural network-based financial risk warning model constructed in this article and traditional statistical methods in terms of accuracy in financial risk prediction. From the figure, it can be clearly seen that compared to traditional statistical methods, the model proposed in this paper demonstrates higher accuracy in financial risk prediction. This advantage is mainly due to the powerful ability of Bayesian neural networks to handle complex nonlinear relationships and uncertainties. By introducing Bayesian inference, this model can fully utilize prior information and sample data to conduct more accurate quantitative analysis of financial risks.

Meanwhile, the nonlinear activation function of neural networks enables the model to capture potential patterns and features in financial time series, thereby improving the accuracy and reliability of predictions. In addition, the model in this article also considers the multidimensional and complex nature of financial risks. By constructing a neural network structure that includes multiple input nodes and hidden layers, synchronous analysis and comprehensive judgment of multiple risk warning indicators are achieved. This multidimensional and comprehensive analysis method helps to more comprehensively evaluate the financial risk situation and provide more scientific decision-making basis for investors and regulatory agencies. In summary, the comparison results in Figure 1 fully demonstrate the significant advantage of the financial risk warning model constructed based on Bayesian neural network in prediction accuracy, providing new ideas and methods for financial risk management and prevention.

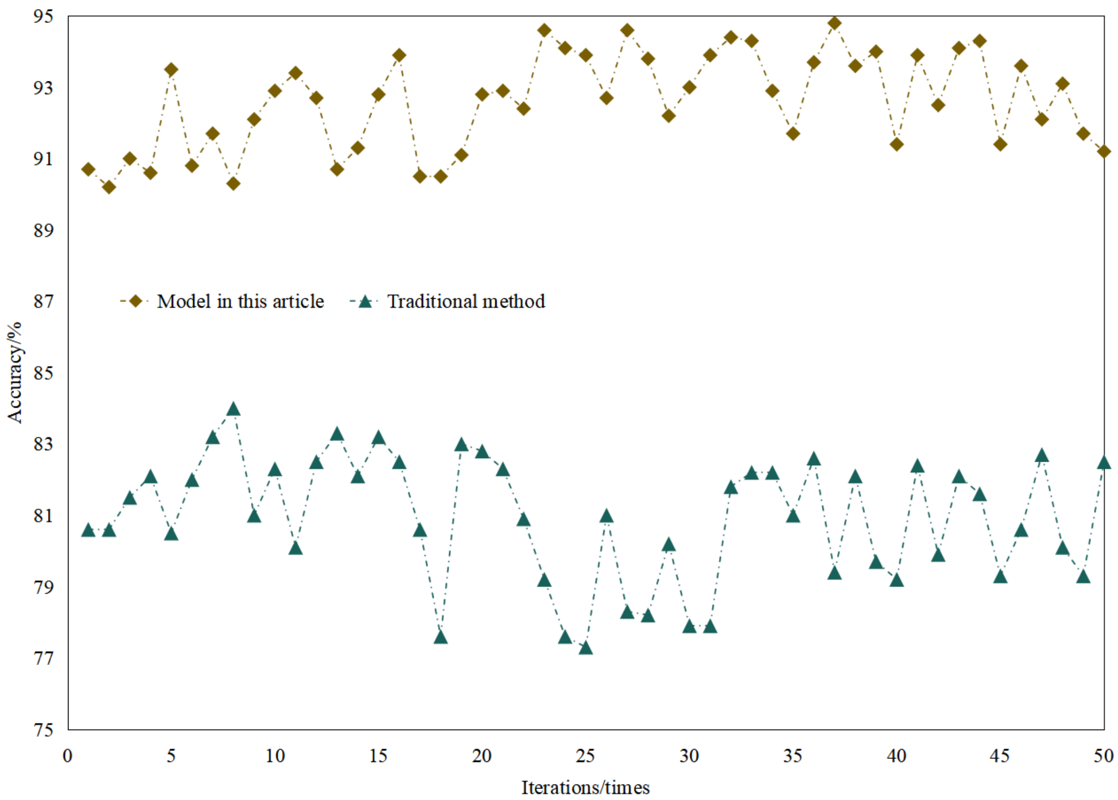

Figure 1 Accuracy comparison

3.2. Error Rate Comparison

Figure 2 provides a detailed comparison of the error rate between the financial risk warning model constructed based on Bayesian neural network and traditional statistical methods in financial risk prediction. It can be clearly seen from the figure that compared to traditional statistical methods, the model proposed in this paper performs better in terms of prediction error rate, with a significant reduction in error rate. This achievement is attributed to the efficiency and accuracy of Bayesian neural networks in processing complex financial data. By introducing Bayesian inference mechanism, this model can fully utilize prior knowledge and sample data to provide more precise characterization and prediction of financial risks. Meanwhile, the nonlinear processing capability of neural networks enables the model to capture potential patterns and dynamic features in financial time series, thereby improving the accuracy and stability of predictions.

In addition, the model in this article fully considers the multidimensional and complex nature of financial risks during the construction process. By designing a reasonable network structure and parameter settings, it achieves comprehensive analysis and evaluation of multiple risk warning indicators. This multidimensional and comprehensive prediction method helps to more accurately reflect the actual risk situation of the financial market, providing more reliable decision support for investors and regulatory agencies. In summary, the comparison results in Figure 2 fully demonstrate the significant advantages of the financial risk warning model constructed based on Bayesian neural network in terms of prediction error rate, further verifying the effectiveness and reliability of the model in the field of financial risk prediction. This research achievement not only provides new technological means for financial risk management and prevention, but also provides strong guarantees for the healthy development of the financial market.

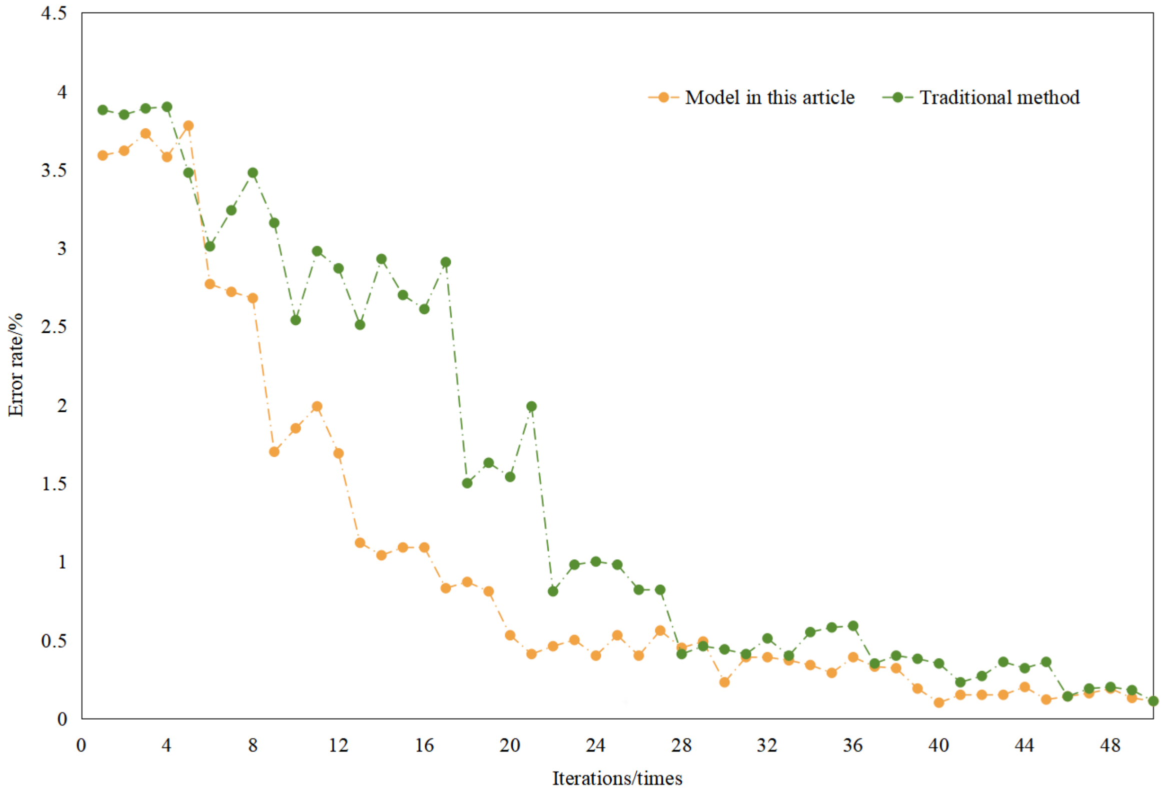

Figure 2 Comparison of error rates

4. Conclusions

The statistical prediction based on Bayesian method has shown broad application prospects and profound research value in the field of financial data analysis. This method cleverly integrates historical data, prior knowledge, and current observation data to provide more accurate and reliable prediction results and risk assessment for financial practitioners, thereby helping them make wiser and more robust decisions. This article deeply analyzes the specific application of Bayesian methods in financial data analysis. By carefully constructing Bayesian models, we have successfully achieved quantitative analysis of various risks in the financial market. This model can not only help us accurately capture market dynamics, but also effectively deal with the non-linear, non-stationary and other complex features in financial data, significantly improving the accuracy and timeliness of risk early warning. In addition, Bayesian methods have strong flexibility and scalability, and can be continuously optimized and improved with the continuous changes in financial markets and the accumulation of data. This means that Bayesian methods will continue to play an important role in future financial data analysis, contributing more to the stable development of financial markets and effective prevention and control of financial risks.

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